



The Role of Machine Learning in Seismic Attribute Analysis: A Commentary on Progress, Pitfalls, and the Path Forward

Okechukwu Frank Adizua*

Geophysics Research Group – GRG,
Department of Physics, Faculty of Science,
University of Port Harcourt,
Port Harcourt,
Rivers State, Nigeria.

Ejikeme ThankGod Anele

School of Foundation Studies,
Rivers State College of Health Science and Management Technology,
Port Harcourt,
Rivers State, Nigeria.

Abstract: The accuracy of conventional reservoir models is sometimes limited by conventional seismic attribute analysis's inability to resolve intricate, non-linear subsurface relationships. In order to minimize exploration risk and optimize recovery, data-driven strategies must be integrated as exploration moves toward structurally complex and mature areas. In order to improve subsurface imaging and reservoir characterization, this commentary paper explores the revolutionary role of machine learning (ML) in seismic attribute analysis. In particular, it assesses how sophisticated workflows maximize pattern detection and close gaps in trans-disciplinary data. We examine the use of important machine learning (ML) architectures in conjunction with cross-disciplinary geological, geophysical, and engineering datasets, concentrating on the advantages and deployment constraints of artificial neural networks (ANNs) and support vector machines (SVMs). According to the analysis, ML algorithms are able to accurately predict important rock qualities like porosity and fluid saturation while also correctly identifying tiny structural elements. This commentary paper also demonstrates the need of tackling the fundamental issues of data quality, interpretability of models, and computational scalability. Finally, we show that a more thorough, dependable, and scalable framework for contemporary reservoir characterization is produced by integrating ML with physics-based restrictions.

Keywords: *Machine learning, Seismic attributes reservoir characterization, Neural networks, Quantitative interpretation.*

Received: 15 March 2025; **Accepted:** 20 April 2025; **Published:** 13 May 2025

I. INTRODUCTION

For more than 50 years, reflection geophysics and subsurface exploration have relied heavily on seismic attribute analysis [1, 2]. The field has developed to include intricate volumetric transformations, starting with early

post-stack structural tracking via basic amplitude and phase variations. These include geometric characteristics that geoscientists extract to identify complicated stratigraphic features and geological anomalies, such as coherence, spectral decomposition, curvature, and Grey Level Co-Occurrence Matrix (GLCM) textures [3, 2]. Deter-

*Correspondence concerning this article should be addressed to Okechukwu Frank Adizua, Geophysics Research Group – GRG, Department of Physics, Faculty of Science, University of Port Harcourt, Port Harcourt, Rivers State, Nigeria. E-mail: okechukwu.adizua@uniport.edu.ng
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ministic empirical approaches have historically played a major role in the interpretation of these qualities. In order to deduce lithological changes or track lateral structural trends, human interpreters manually linked individual seismic reflections with limited well-log data [4].

However, when dealing with non-linear geological variables, traditional quantitative interpretation (QI) and traditional multi-attribute regression operations reach a rigorous mathematical ceiling [5]. The subsurface of the Earth is intrinsically multi-scale, an-isotropic, heterogeneous, and noise-contaminated. The extremely complex, subtle variations in wave propagation produced by localized changes in porosity, lithology, and fluid saturation cannot be adequately captured by simple linear multi-attribute regressions or single-attribute transformations [6]. As a result, delicate reservoir compartments, thin-bedded sands, or small sub-seismic fault networks that control dynamic fluid flow are often ignored by conventional procedures.

Asset teams are experiencing an information overload due to the emergence of the contemporary "Digital Oilfield" and rapid developments in high-density 3D and 4D seismic acquisitions [7]. Massive, high-dimensional datasets with hundreds of distinct seismic characteristics are produced by contemporary seismic surveys. According to La Marca Molina and Marfurt (2022) [8], standard human-centric visual analysis is no longer quick enough, scalable enough, or granular enough to securely process enormous data quantities or methodically find correlations within the attribute space. A crucial paradigm shift has been made possible by this structural bottleneck: the use of machine learning (ML) as a fundamental interpreter's tool. By leveraging advanced data-driven architectures, modern geophysicists can rapidly automate feature extraction, discover implicit non-linear attribute cross-correlations, and dramatically accelerate the accuracy of static reservoir characterization [5, 7].

II. RATIONALE: WHY MACHINE LEARNING IS IMPERATIVE

Rapidly depleting mature assets, structurally complex deep water plays, and extremely thin economic margins characterize the operational landscape that the global oil business is currently navigating [9]. Optimizing the technical value and predictive potential of current seismic data volumes is now a business necessity rather than an optional luxury in this extremely unstable economic situation. The entire range of geological information contained within the acoustic wave field is not extracted by conventional workflows that treat seismic data separately. These implicit, hidden patterns inside multi-attribute data

spaces that are not visible to the human eye can be isolated, analyzed, and extracted using machine learning's multi-dimensional mathematical machinery [8, 7].

Importantly, contemporary artificial intelligence frameworks rely on traditional seismic properties as fundamental building pieces rather than attempting to replace them. Root-mean-square (RMS) amplitude, sweetness, sweetness-gradient, and structural curvature are examples of seismic features that act as suitable transformations to enhance subsurface discontinuities, frequency attenuation, and elastic sensitivities [3, 2]. These characteristics serve as highly optimized, engineered features in the context of data science. According to Abdul-Fattah et al. (2020) [5], feeding these pre-computed features into machine learning models significantly speeds up algorithm training, enhances mathematical convergence, and increases the resolution of final predictions.

Machine learning effectively closes the long-standing gap between qualitative geomorphology and quantitative petrophysics by processing high-dimensional data spaces concurrently [4]. Cognitively, human interpreters can only use color-blending strategies to visualize three or four qualities at once. On the other hand, sophisticated computers can easily analyze dozens of attribute cubes at once, spotting minute statistical interactions that point to regional variations in reservoir quality [10]. The naive, idealistic presumptions included in traditional linear rock-physics templates are entirely avoided by this methodology. They are replaced by adaptable, reliable, non-linear mapping techniques that can directly forecast complicated rock properties from raw amplitude fluctuations and respect lateral reservoir heterogeneity [9, 6].

III. ALGORITHM ARCHITECTURES: CAPABILITIES AND CONSTRAINTS

A wide range of computer architectures are necessary for the application of machine learning in seismic attribute analysis. The particular geological aim, the amount of training data available, and the intrinsic mathematical limitations of each algorithm family must all be balanced when choosing the right model.

A. Support Vector Machines (SVM) & Support Vector Regression (SVR)

Support vector machines use mathematical kernel functions to project lower-dimensional seismic attribute data into higher-dimensional spaces, creating the best hyperplane for feature classification or continuous property prediction [9]. In frontier basins with patchy well-log control, this design works remarkably well for quantitative rock attribute prediction, such as estimating Acous-

tic Impedance, rock density, or Total Organic Carbon (TOC) [11]. Unsupervised clustering algorithms, like Self-Organizing Maps (SOM), are often used in conjunction with SVM workflows to divide multi-attribute spaces into foundational lithofacies categories prior to regression when labeled well data are completely lacking [8, 10].

1) *Capabilities*: Strong mathematical resilience, avoidance of local minima, and exceptional generalization with tiny, sparse training datasets—where deep learning would falter—are among its strengths.

2) *Constraints*: The model's performance is extremely sensitive to the regularization settings and kernel function selection; it is computationally demanding and scales poorly when applied to billions of individual grid cells within enormous 3D seismic volumes.

B. Artificial Neural Networks (ANN) & Deep Learning

As universal function approximators, Multi-layer Perceptrons (MLPs) and Deep Neural Networks (DNNs) use layers of connected nodes to find non-linear correlations. ANNs are used in reservoir characterization to directly map multi-attribute arrays to continuous petrophysical goals measured at the well bore, such as spectrum decomposition, instantaneous frequency, and root-mean-square (RMS) amplitude [5, 4]. Large-scale subsurface foundation models, which employ deep learning topologies to carry out multi-task learning across extensive, multi-basin regional datasets, have been developed recently from these networks ([7].

1) *Capabilities*: Captures abrupt, non-linear petrophysical or lithological changes throughout a reservoir and has an unparalleled capacity to simulate extremely complex, multi-variable physical systems [6].

2) *Limitations*: Large, varied calibration datasets are needed to produce stable weight distributions; there is a high risk of over fitting, when the network memorizes acquisition footprints or ambient seismic noise instead of

real geological patterns.

C. Convolutional Neural Networks (CNN)

In contemporary seismic interpretation workflows, CNNs are an established and revolutionary sub-application. CNNs process limited spatial patches, considering 2D seismic slices or 3D sub-volumes as digital images, as opposed to single data points, independent traces, or isolated well sites [12]. The network can automatically extract geometric features and hierarchical texture from the data as a consequence of its spatial awareness. This closely resembles how human interpreters assess depositional patterns, structural dip, and lateral continuity [13].

1) *Capabilities*: Exceptionally effective in multi-horizon tracking, salt-dome boundary detection, and automated structural fault segmentation [12, 13]. Using a small number of user-provided interpretation anchors, modern CNN implementations enable the model to learn spatial geometric bounds dynamically, quickly spreading the interpretation throughout the entire survey [14, 15].

2) *Limitations*: Depends largely on enormous amounts of carefully labeled training data to avoid spatial bias; requires massive computational infrastructure, usually requiring distributed GPU processing.

D. Multidisciplinary Integration

An important technological and financial asset liability is a data science model that operates in a computational vacuum. Machine learning workflows must be closely integrated throughout the whole asset lifespan, bringing diverse disciplines together inside a collaborative loop, in order to deliver true commercial value [9, 7]. Because of the intrinsic complexity of the subsurface, geophysics, geology, and reservoir engineering must all simultaneously honor data-driven predictions [5]. As shown in Figure 1, machine learning serves as a pivot at the intersection of these disciplines.

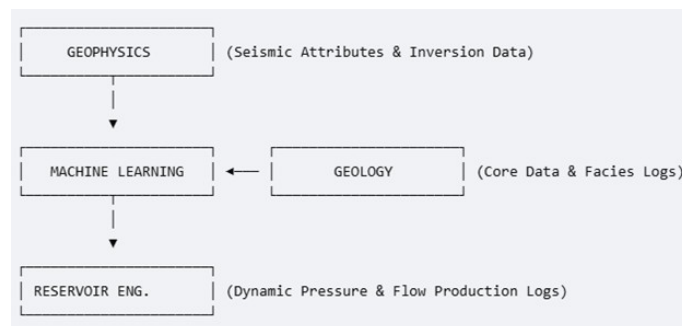


Fig. 1. A workflow showing machine learning as an intersection point for geophysics, geology and reservoir engineering disciplines

1) *Geophysics*: This field provides the machine learning pipeline's fundamental structure. It offers pre-stack inversion data, such as shear and acoustic impedance, post-stack structural and strati-graphic characteristics, and base spatial data cubes [1, 11]. The regional spatial dimensions and structural limitations that the algorithms function within are established by these data volumes.

2) *Geology*: In order to train and test supervised machine learning models, geologists supply the crucial ground-truth calibration points. Physical core samples, thin-section petrography, biostratigraphical information, and well-log faces classifications are all integrated in this process [10]. A machine learning model lacks the contextual constraints required to correctly distinguish between mathematical anomalies and actual depositional changes in the absence of these

3) *Reservoir Engineering*: Comparing an AI-driven static reservoir model with dynamic subsurface performance provides the final validation. Important dynamic datasets, including as production flow rates, bottom-hole pressure declines, tracer tests, and well-test transience, are provided by reservoir engineers [16]. A predicted high-porosity "sweet spot" can be verified as either a physically drain-able, highly permeable accumulation or an isolated mathematical artifact by aligning the machine learning-generated predictive maps with real fluid flow patterns [9, 17].

The machine learning model is kept rooted in physical realities as a consequence, to this integrated loop. Asset teams can create a single subsurface model by integrating the vertical resolution of well-bore geology, the spatial coverage of seismic characteristics, and the dynamic validation of reservoir engineering [5, 17]. By using a multidisciplinary approach, the danger of drilling dry or non-commercial development wells is reduced and geographic uncertainty is greatly reduced.

IV. THE TRIPLE CHALLENGE: OBSTACLES TO WIDESPREAD ADOPTION

Even while using machine learning in seismic attribute workflows has obvious mathematical benefits, there are a number of significant obstacles preventing its systematic, broad adoption in the energy sector. These barriers fall into three main categories: cross-basin scalability, model interpretability, and data conditioning.

A. Data Quality & Conditioning

One of the greatest obstacles in geophysics is still a basic principle of scientific computing: "Garbage In, Garbage Out." Environmental ambient noise, multi-path reflections, acquisition footprints, wave attenuation, and

intricate processing artifacts are inherent problems with raw seismic data [12]. Supervised machine learning algorithms, especially deep neural networks, sometimes confuse processing fingerprints or noise for real geological abnormalities due to their extreme sensitivity to minute amplitude and phase distortions [7]. Advanced deep learning denouncing frameworks are increasingly needed to preload raw amplitudes prior to attribute extraction in order to mitigate this. Well-log calibration and rigorous, amplitude-preserving seismic processing are still very costly, time-consuming, and non-negotiable requirements [4, 11]. If the underlying data quality is compromised, the algorithm will yield highly precise but geophysical invalid predictions.

B. Interpretability (The Black Box Problem)

Conventional deep learning architectures function as extremely intricate "black boxes," providing neither a clear mathematical explanation nor a physical explanation for why a given combination of seismic characteristics results in a specific petrophysical forecast [16]. A recommendation based only on the internal weights of an algorithm is an unacceptable technical risk for multidisciplinary asset teams risking millions of dollars on a single exploration or deep water development well. Explainable AI (XAI) is being aggressively adopted in modern geophysics to close this critical trust gap [18, 16]. To dissect these models, techniques like Shapely Additive explanations (SHAP) values and Local Interpretable Model-agnostic Explanations (LIME) are being actively used. These XAI tools calculate the exact feature importance of individual input attributes—such as quantifying how much coherence vs. spectral decomposition drives a localized fault or faces classification—thereby bringing empirical accountability to data-driven subsurface mapping [16].

C. Scalability & Infrastructure

When applied to a regional basin spanning thousands of square kilometers, an algorithm that exhibits perfect predictive accuracy when trained on a localized, high-density datasets covering a single oilfield sometimes fails [14, 7]. Massive computational infrastructure, such as distributed multi-GPU acceleration, elastic cloud computing environments, and highly optimized data management pipelines, is needed to manage multi-terabyte 3D and 4D seismic volumes [13]. Additionally, when applied to other geological domains, machine learning models show poor generalization ability. It is impossible to reliably scale or deploy a convolutional neural network that has been painstakingly trained to identify structural features

in a conventional offshore carbonate reservoir to predict properties in highly heterogeneous unconventional shale or complex coal-bed methane blocks without suffering from significant performance degradation [9, 19]. This lack of universal portability remains a major barrier to routine industrial scalability.

V. DISCUSSION: THE PARADIGM SHIFT TO PHYSICS-INFORMED ML

Modern geophysics is undergoing a significant paradigm change toward Physics-Informed Neural Networks (PINNs) in order to address the severe generalization constraints, data sensitivity, and black-box character of unconstrained data-driven models. Without any prior

knowledge of geology or wave physics, purely statistical machine learning algorithms approach seismic attribute analysis as a blind mapping exercise, finding mathematical relationships. When used outside of its immediate calibration well boundaries, an unconstrained model often produces geophysical impossible predictions, such as negative porosity, inverted densities, or fluid saturation that defy mass balance equations, even though it may achieve a low root-mean-square error (RMSE) on a localized training datasets. Figure 2 shows that the optimal model should be such that bridges both seismic attribute data with physics laws (physical laws of wave mechanics and geology) to produce geologically validated results.

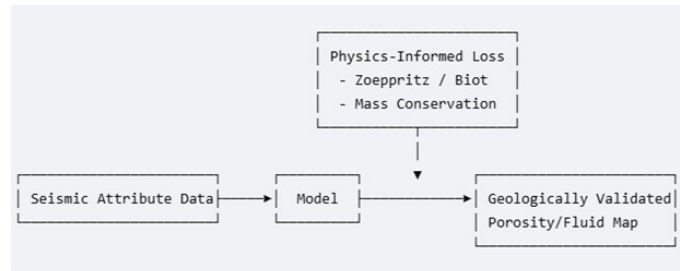


Fig. 2. An optimal machine learning model should integrate both seismic attribute data with physics laws to yield geologically consistent results.

PINNs resolve this fundamental vulnerability by embedding known physical laws, rock physics templates (RPTs), and deterministic wave equations directly into the neural network's architecture and optimization loops. The core innovation lies in modifying the algorithm's objective function. Instead of minimizing a standard statistical loss function alone (such as Mean Squared Error based strictly on well-log training labels), the total loss $Loss_{Total}$ is formulated as a multi-task learning problem:

$$Loss_{Total} = w_1 Loss_{Data} + w_2 Loss_{Physics} \quad (1)$$

Where $Loss_{Data}$ represents the empirical error at the well bore control points, while $Loss_{Physics}$ penalizes any model prediction that violates fundamental scientific principles and laws (with w_1 and w_2 acting as balancing weights). Depending on the specific target of the reservoir characterization workflow, several foundational physical equations are utilized to construct $Loss_{Physics}$.

Some of the foundational physical equations are briefly presented below:

Some of the foundational physical equations are briefly presented below:

A. Wave Propagation and Zoeppritz Equations

The network is limited by the Zoeppritz equations or their linear approximations (such as Aki-Richards formulations) when the model seeks to forecast acoustic and shear impedance from pre-stack amplitude variation with offset (AVO) properties. This guarantees that realistic reflection coefficients and wave propagation mechanics are reflected in the generated impedance volumes.

B. Gassmann Fluid Substitution & Biot Theory

The Gassmann equations constrain the network's loss function for forecasting pore fluids, fluid saturation, and rock frame compressibility. The physics loss increases dramatically if the model forecasts a particular porosity and fluid saturation combination that, according to rock physics, results in an impossible bulk modulus. This forces the network weights to change in the direction of a physically sound solution.

C. Geomechanical and Porosity Constraints

To strictly limit porosity predictions between 0% and the critical porosity limit of the particular depositional facies, the algorithm can be explicitly bounded by empirical rock-physics boundaries (e.g., Wyllie time-average equations or the Hashin-Shtrikman bounds).

For contemporary reservoir characterisation, this integration offers three significant benefits. It significantly lessens reliance on data, to start. PINNs are perfect for frontier exploration basins because they require much fewer marked well-log calibration spots to produce high-accuracy forecasts because the physical equations function as a continuous spatial guide. Secondly, it guarantees reliable extrapolation. The model is physically prevented from producing extremely irregular or implausible trends if an exploration asset team uses a PINN methodology in an undrilled, deeper compartment of a sedimentary basin, guaranteeing a trustworthy baseline evaluation. Thirdly, it closes the trust gap. PINNs give asset teams the scientific assurance needed to make crucial, high-stakes drilling and field development choices by substituting a workflow rigorously guided by accepted earth science principles for arbitrary data-mining techniques [5, 9].

VI. CONCLUSION

More than just a small software update, the incorporation of machine learning into seismic attribute analysis represents a fundamental paradigm shift in the way the energy sector performs quantitative subsurface imaging and reservoir characterization [5, 7]. Data-driven workflows have evolved from an academic luxury to an operational need as exploration continues to shift toward structurally challenging deep water plays and mature, highly depleted fields. The current state of AI-driven geophysics is defined by a number of crucial trends, capabilities, and structural bottlenecks that have been emphasized in this commentary paper:

A. Advanced Feature Mapping

Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and Convolutional Neural Networks (CNNs) are examples of contemporary machine learning architectures that have an unparalleled capacity to resolve intricate, non-linear subsurface linkages [9]. These models greatly increase the predictive accuracy of continuous petrophysical rock properties like porosity and fluid saturation, resolve subtle depositional geometries, and quickly speed up the detection of sub-seismic faults by treating pre-computed seismic attributes as highly engineered spatial features [12, 6].

B. The Multidisciplinary Mandate

Data science cannot function in a vacuum. Any machine learning model's technical and economic success is solely dependent on its smooth integration throughout a cooperative loop of dynamic reservoir engineering, well-bore geology, and geophysics [17]. A geologically com-

patible model supported by dynamic fluid flow parameters is left behind after statistical mathematical abnormalities are eliminated thanks to this structural alignment.

C. Overcoming the Trust and Infrastructure Gaps

The "Triple Challenge" of raw data quality, model interpretability, and cross-basin scalability is now impeding widespread industrial use. By using Explainable AI (XAI) frameworks, particularly LIME and SHAP values, to offer mathematical accountability and transparent feature ranking for multi-million dollar drilling decisions, the industry is actively dismantling the problematic "black-box" nature of deep learning [16].

D. The Physics-Informed Future

The move from solely data-mining statistical models to Physics-Informed Neural Networks (PINNs) represents the biggest paradigm shift in reservoir characterisation going forward. Geoscientists can make algorithms respect physical boundaries by explicitly including foundational equations (such as Zoeppritz, Gassmann, and basic mass-conservation rules) into the neural network's loss function [20, 19]. This hybrid technique guarantees that forecasts are essentially rooted in physical reality, improves spatial extrapolation capabilities, and significantly minimizes reliance on well-log data.

In the end, unrestricted algorithms or fully manual, conventional interpretation methods are not the way of the future for subsurface characterization. Success depends on hybrid systems, which are a well-balanced framework in which human geoscientists' contextual knowledge continuously guides and validates physics-informed machine learning algorithms to perform the high-dimensional computational processes involved in seismic attributes analysis geared towards reservoir characterization.

VII. ACKNOWLEDGMENTS

The authors express their profound gratitude to all the great scholars and scientists whose works provided this commentary paper with the much-needed leverage for which it was anchored upon. Appreciation is also extended to the affiliated institutions for providing platforms for research and teaching.

VIII. CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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